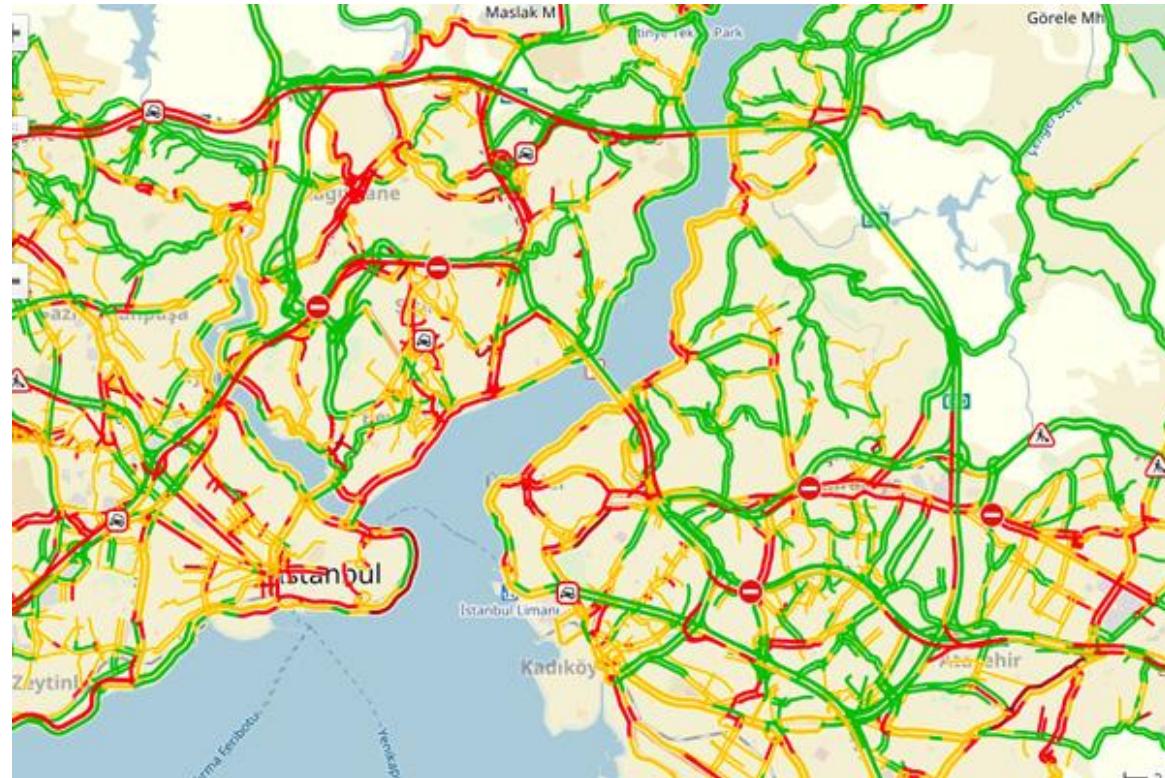


Traffic Congestion and Street Network of Istanbul



Ayse Ozturk • May 2020

On News ...



9. Istanbul, Turkey

Istanbul's already-bad traffic worsened in 2019, with congestion levels hitting 55%, 2 points worse than in 2018.

2. Istanbul, Turkey



7	Lima	Peru	57%	↓ 1%	>
8	New Delhi	India	56%	↓ 2%	>
9	Istanbul	Turkey	55%	↑ 2%	>
10	Jakarta	Indonesia	53%	0%	>
11	Bangkok	Thailand	53%	0%	>

Research Question:

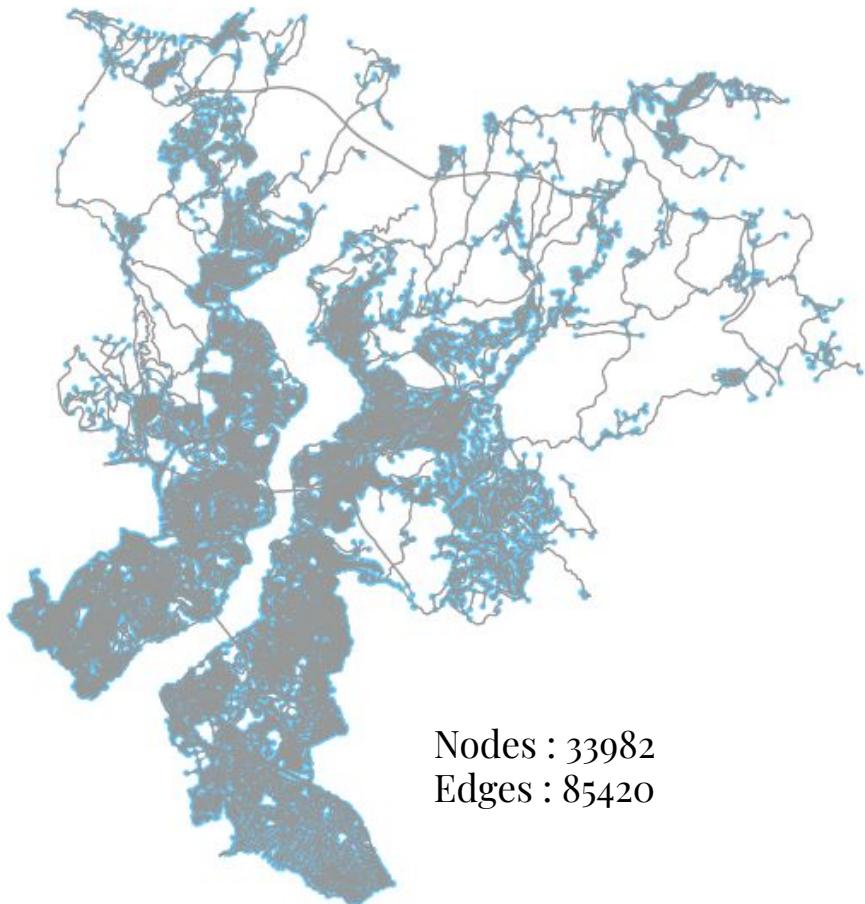
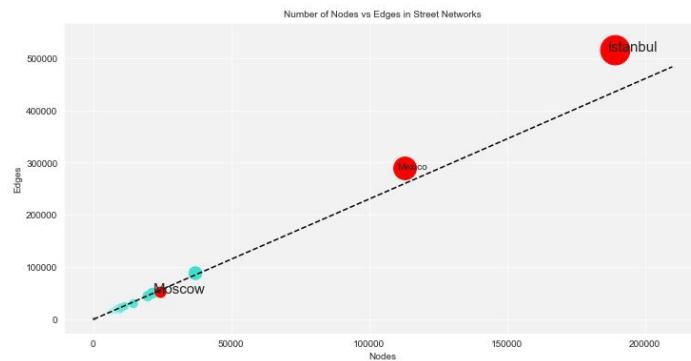
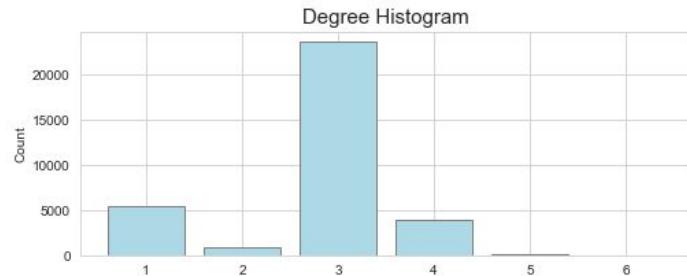
Can we understand traffic congestion using network science tools ?

Relevant Literature:

Scaling Laws in spatial structure of urban roads - Lammer. Et. al.	20 German Cities	Betweenness centrality and congested zones
Centrality Measures in Spatial Networks - Crucitti et. al.	18 Different World Cities	Self Organized Planned Cities
Structural properties of planar graphs of urban street patterns - Cardillo et. al.	20 Different World Cities	Medieval , Grid-iron, Modernist Baroque , Mixed , Lollipop

Method: Compare Istanbul with other cities

1. Planar Network Structure



Introduction

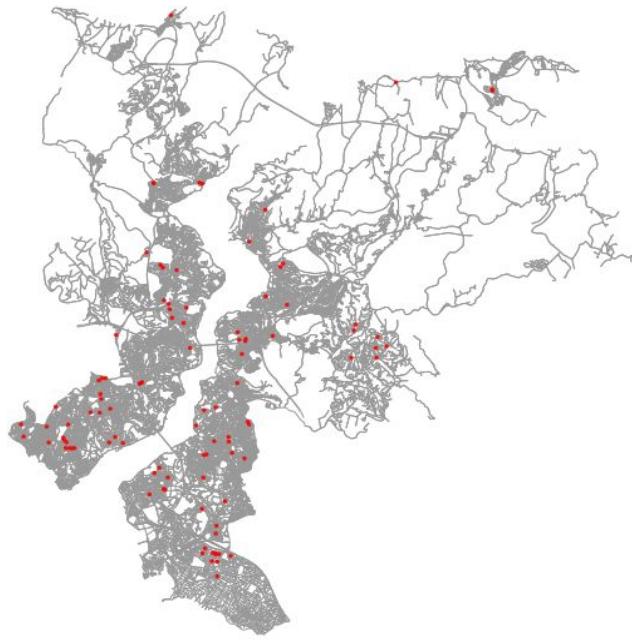
Node and Edge Properties

Centrality Measures

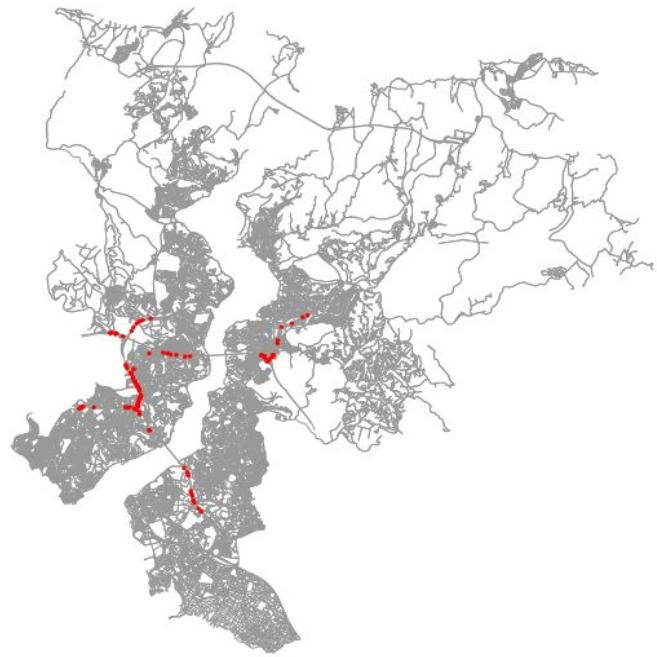
Efficiency

Future Work

2. Degree-Betweenness Centrality Anomaly*



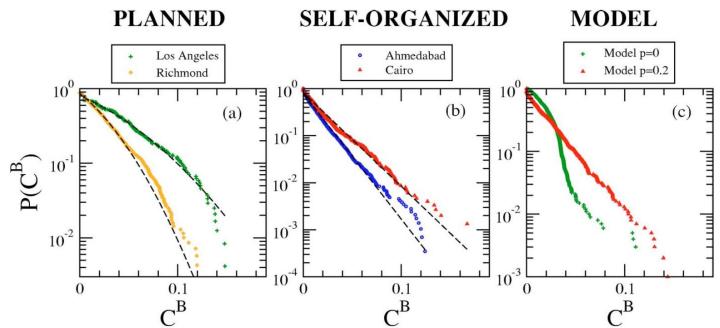
Top 100 Degree Centrality Nodes



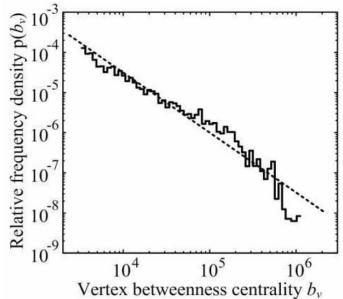
Top 100 Betweenness Centrality Nodes

3. Betweenness Centrality Distribution

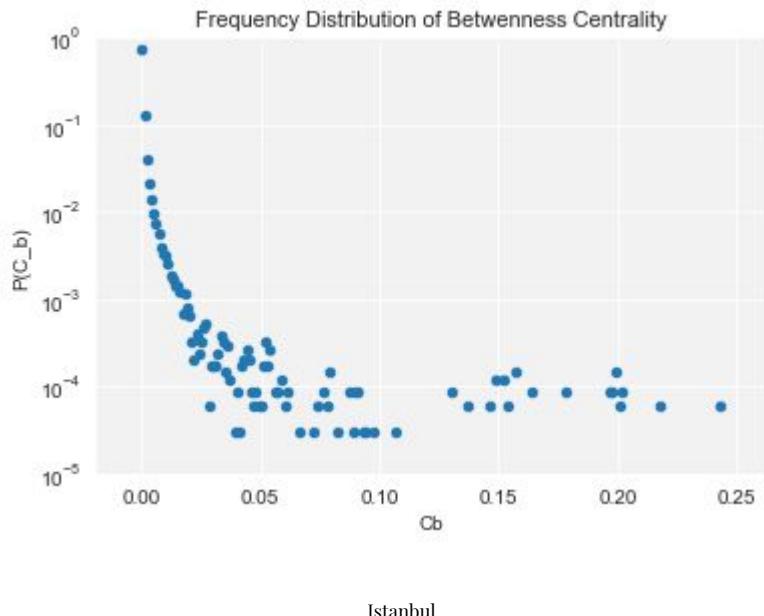
Planned and Self Organized Cities from Crucitti et. al.



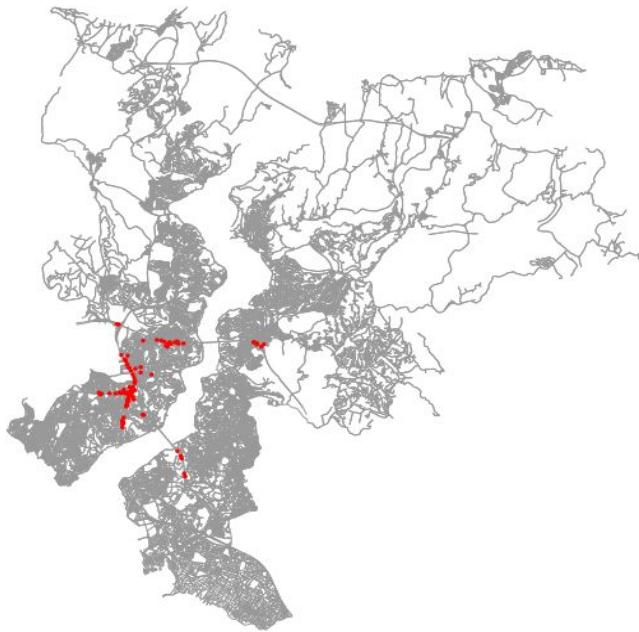
German street network from Lammer et. al.



- Planned City
- Self-Organized City

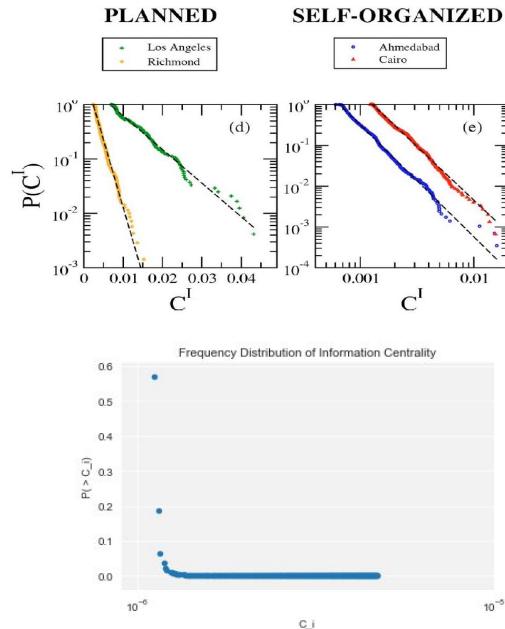


4. Information Centrality Distribution



Top 100 Information Centrality Nodes

Information Centrality: Measures the drop in the network efficiency caused by the removal of the node.



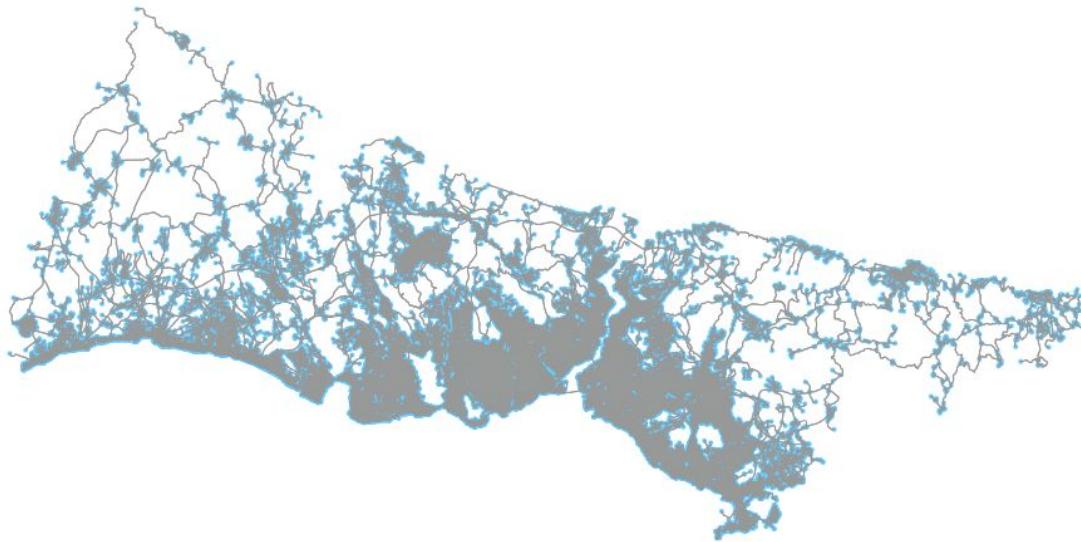
5. Future Work

Understanding the Network:

- Efficiency analysis
- How does road network connect with ferry lines

Designing Network:

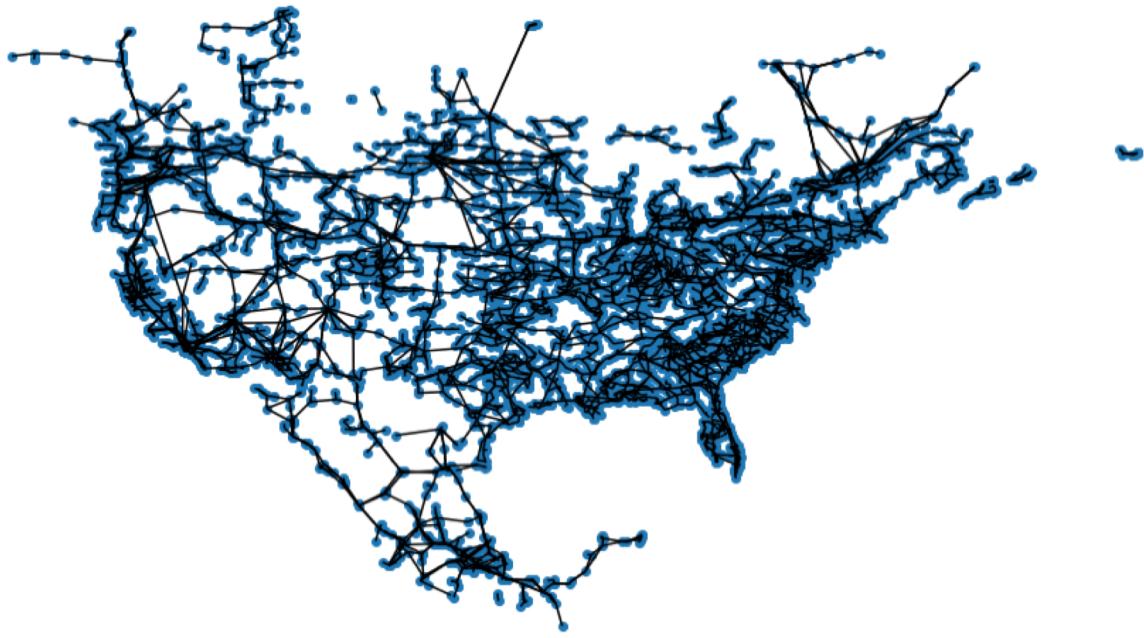
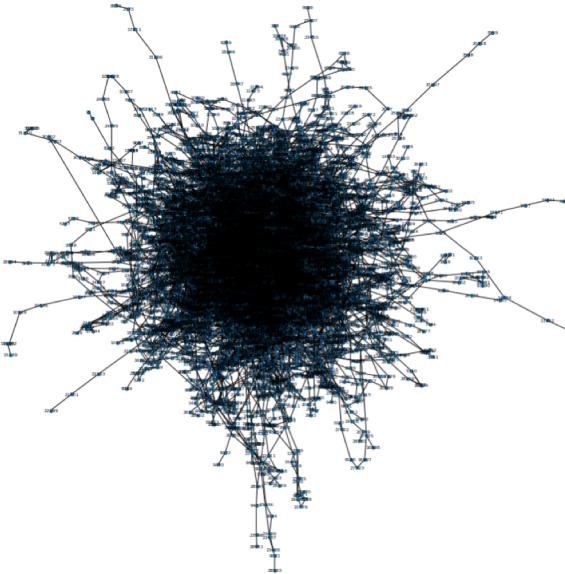
- How can we utilize these metrics in the planning stages



US/NA Power Grid: Analysis of Major Blackouts

Dataset

- Nodes = Electrical components (generators, load buses, etc)
- Edges = Transmission lines

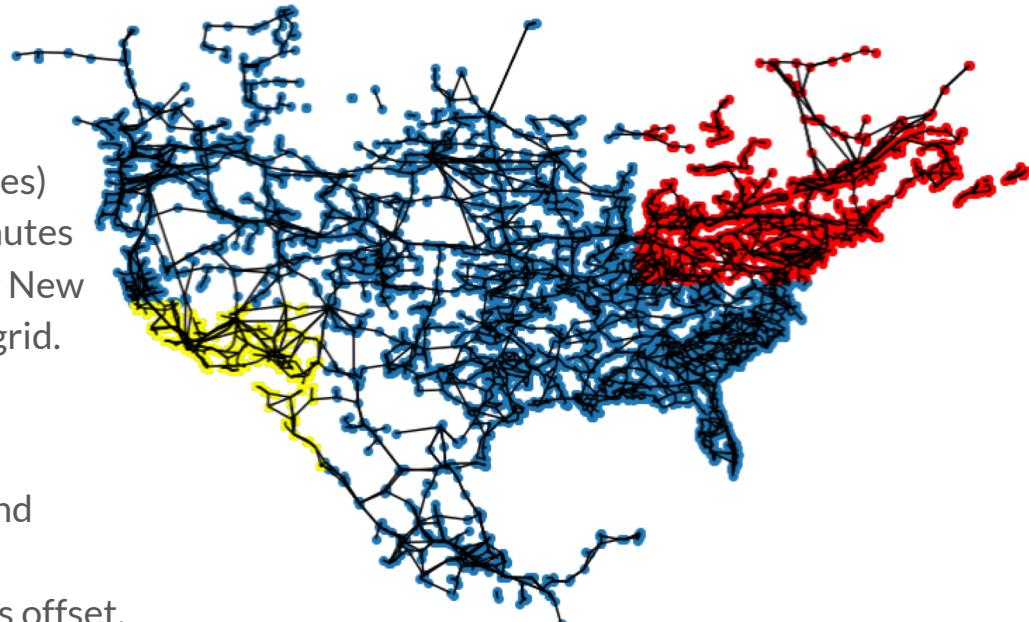


Motivation

- How immune is the current infrastructure to major blackouts?
 - How much of the blame should be put on infrastructure for the 2003 Northeast Blackout and the 2011 Southwest Blackout?

2003 (red)

- Cause: Software bug in grid operator's alarm system in Ohio
- 5 line trips in 3-4 hours (sag and hit trees)
- 256 power plants shut off within 6 minutes after that (Cascading failure) including New York and Ontario disconnecting their grid.



2011 (yellow)

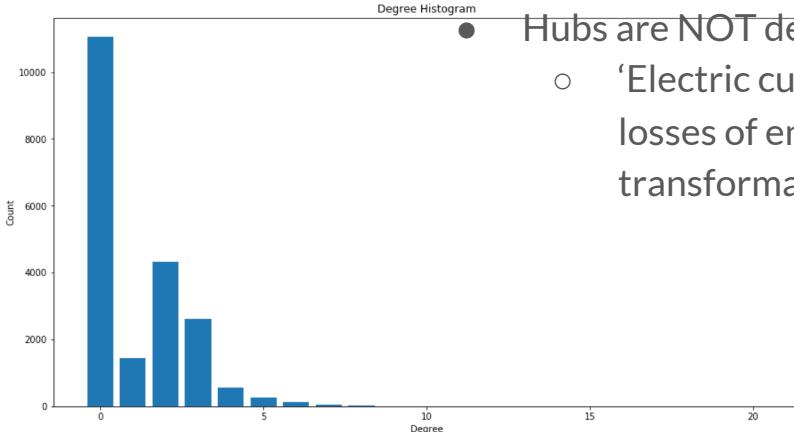
- The one line (500 kV) connecting SD and Arizona shut down --technician error
- Reconnected, but phase difference was offset, resulting in line and transformer overloads

Network Optimization?

- In order to ensure one mishap (line going offline) does not result in cascading failure effect...
 - Minimize path length
 - Optimize closeness centrality score (shorter distances are better)
 - GIVEN - Minimize degree and betweenness centrality

■ Power grid networks are not a 'rich-club' networks (Csigi, M., Kőrösí, A., Bíró, J. et al.)

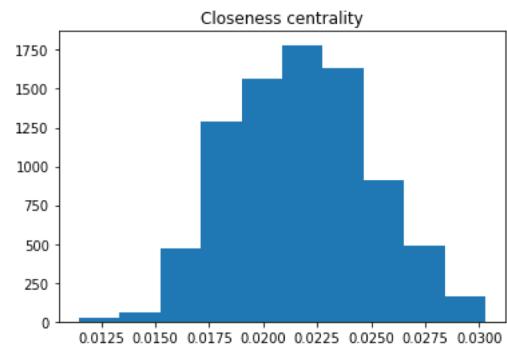
- Hubs are NOT densely connected (very sparse)
 - 'Electric current cannot be transferred efficiently (i.e. without huge losses of energy) over large distances without intermediate transformations at middle stations' => low degree network



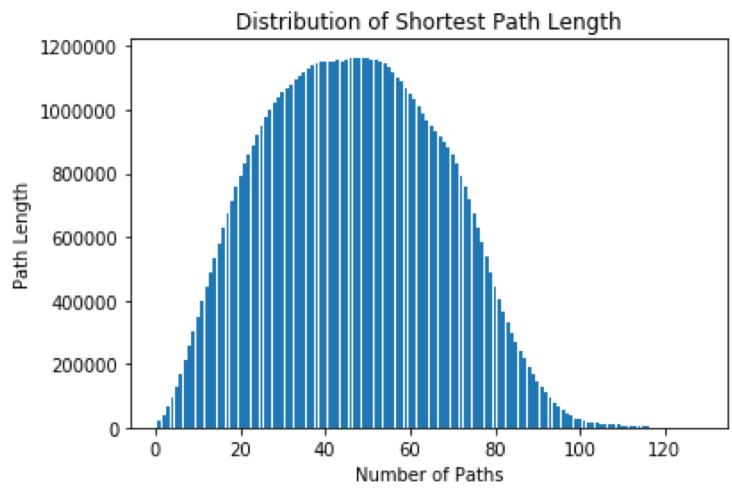
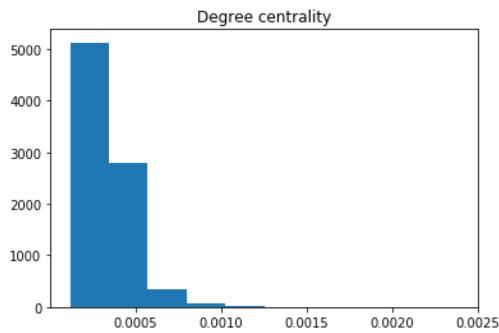
Csigi, M., Kőrösí, A., Bíró, J. et al. Geometric explanation of the rich-club p in complex networks. Sci Rep 7, 1730 (2017).

Network Analysis

	Clustering Coefficient	Avg Shortest path length
North America Power Grid	0.07	46.98

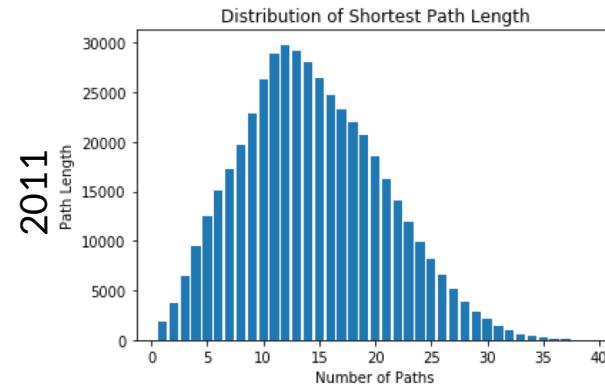
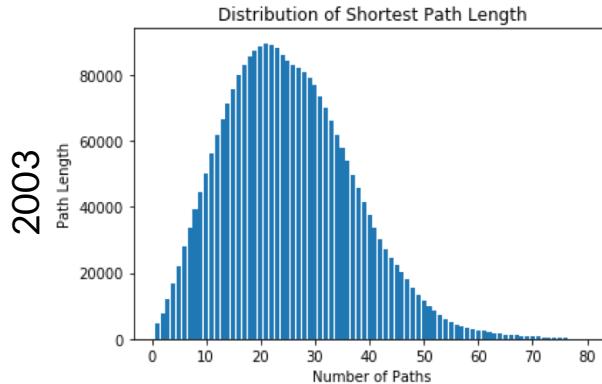


Avg ~ 0.022

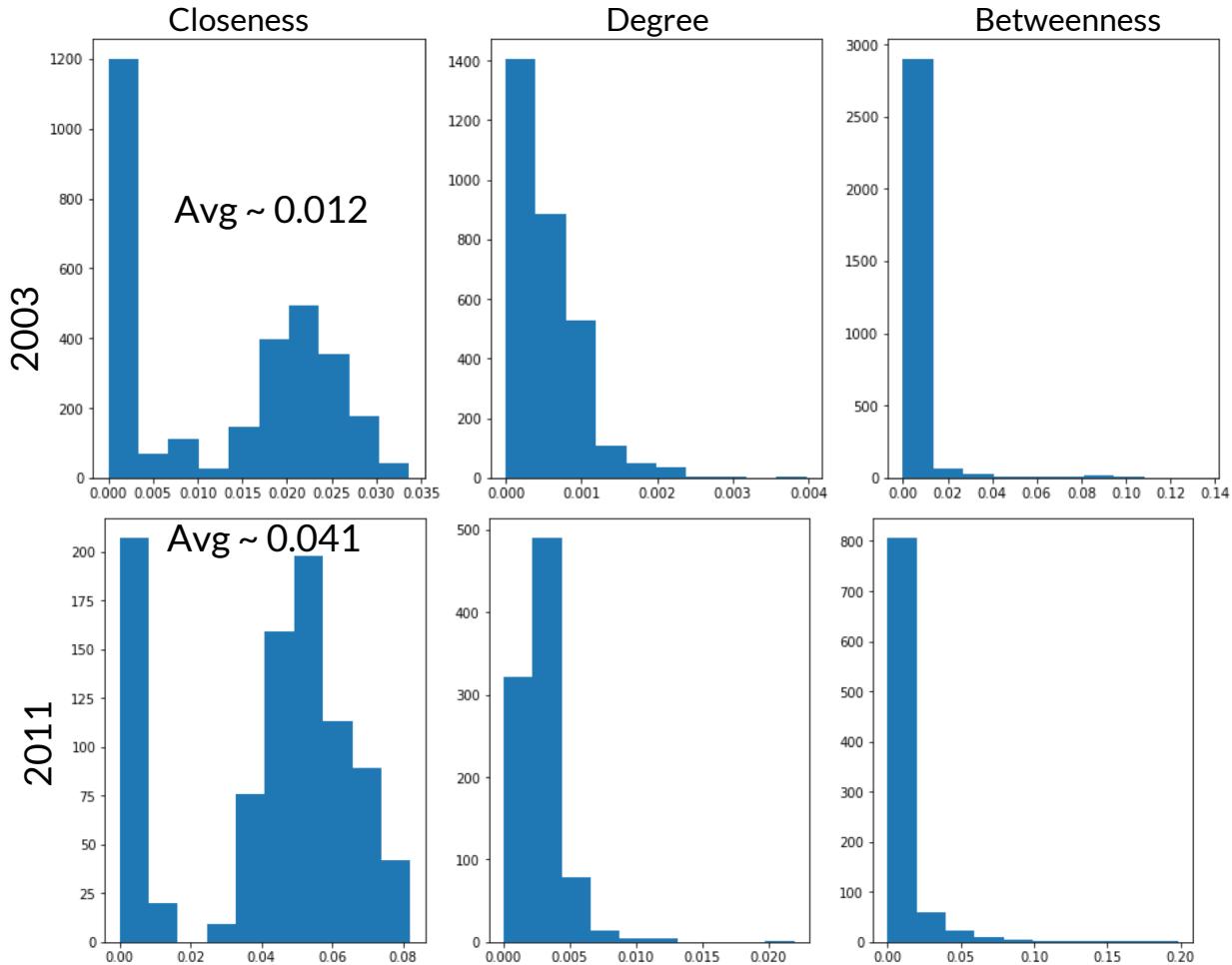
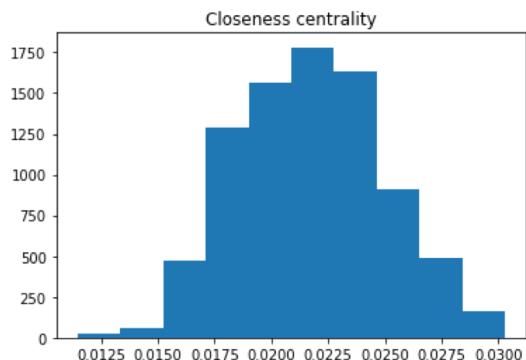


Network Analysis

	Clustering Coefficient	Avg Shortest path length
Non-impacted	0.051	48.00
2003 impacted area	0.053	25.30
2011 impacted area	0.084	14.45



Avg ~ 0.022



Conclusions

- Major blackouts can't be attributed to the infrastructure of the power grid network.
 - Larger average path length does not necessarily mean grid is more susceptible
 - The parameters were way more optimal in the 2011 network, yet it was an area that was hit hard.
 - There are power flow engineers that monitor the grid and can isolate any faults and manage the load accordingly!

Disease transmission dynamics in educational spaces

Alex Zhao

Presentation overview

Key idea

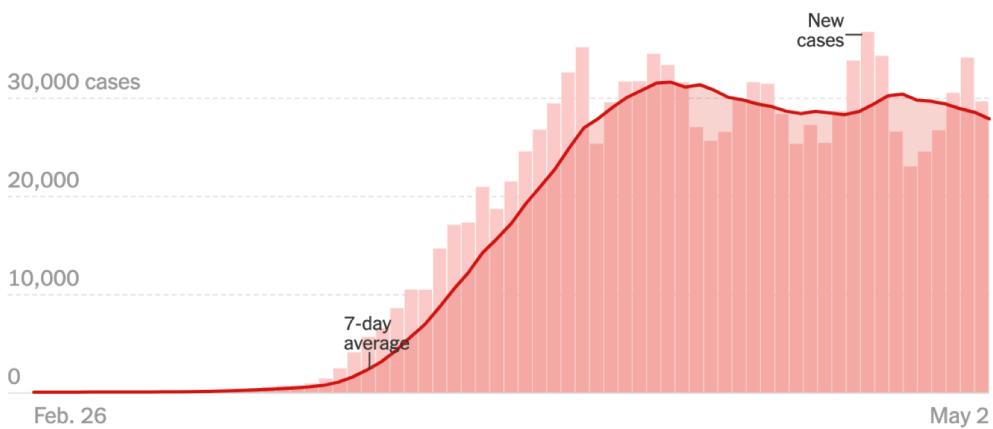
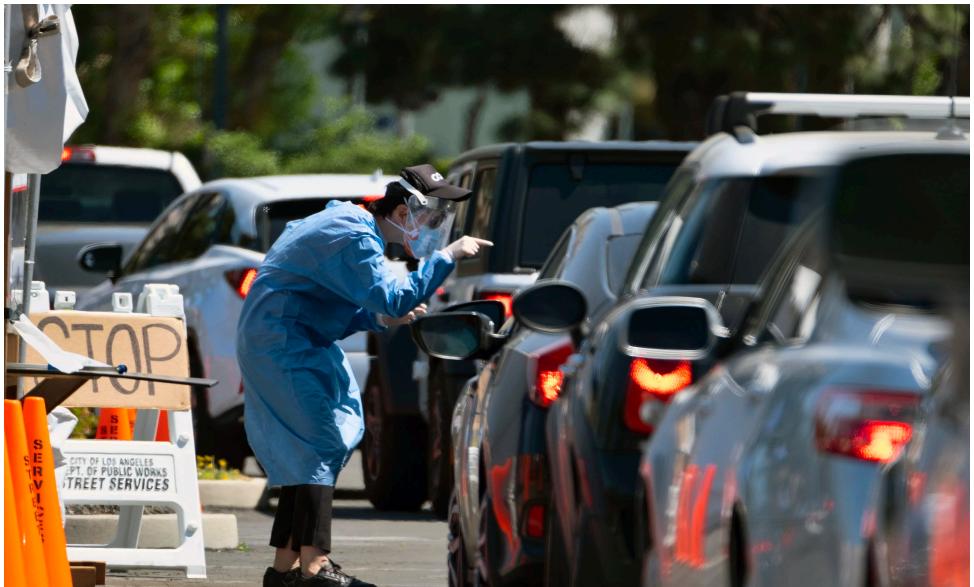
Analyze disease transmission at a single high school to determine best responses for managing epidemics.



- **Methodology** for constructing network using sensor data
- Analyze and **visualize** network properties
- Analyze **centrality** and **shortest paths** in network
- **Simulate** disease transmission
- **Recommend strategies** for combating disease in high schools
- Suggest directions for **future work**

Motivation for study

- Educational spaces like colleges and high schools are compact and **hotbeds for disease**
- COVID-19 shows the importance of **swift responses** by scientists and governments to disease
- And, I'm curious about how **Cal would be affected!**



Constructing the graph

Dataset

- Bluetooth sensor data on interactions from Salathe et al (2010)
- Resulting graph is **undirected** since interactions are symmetric
- Many more edges than nodes

Nodes

- Individuals at the school. Includes administrators, students, and staff
- Number of nodes: 788

Edges

- Any interaction between two individuals for more than 5 minutes
- Edge weight is determined by the **number of interactions**, not duration
- Number of edges: 118,291

Community analysis: Louvain method

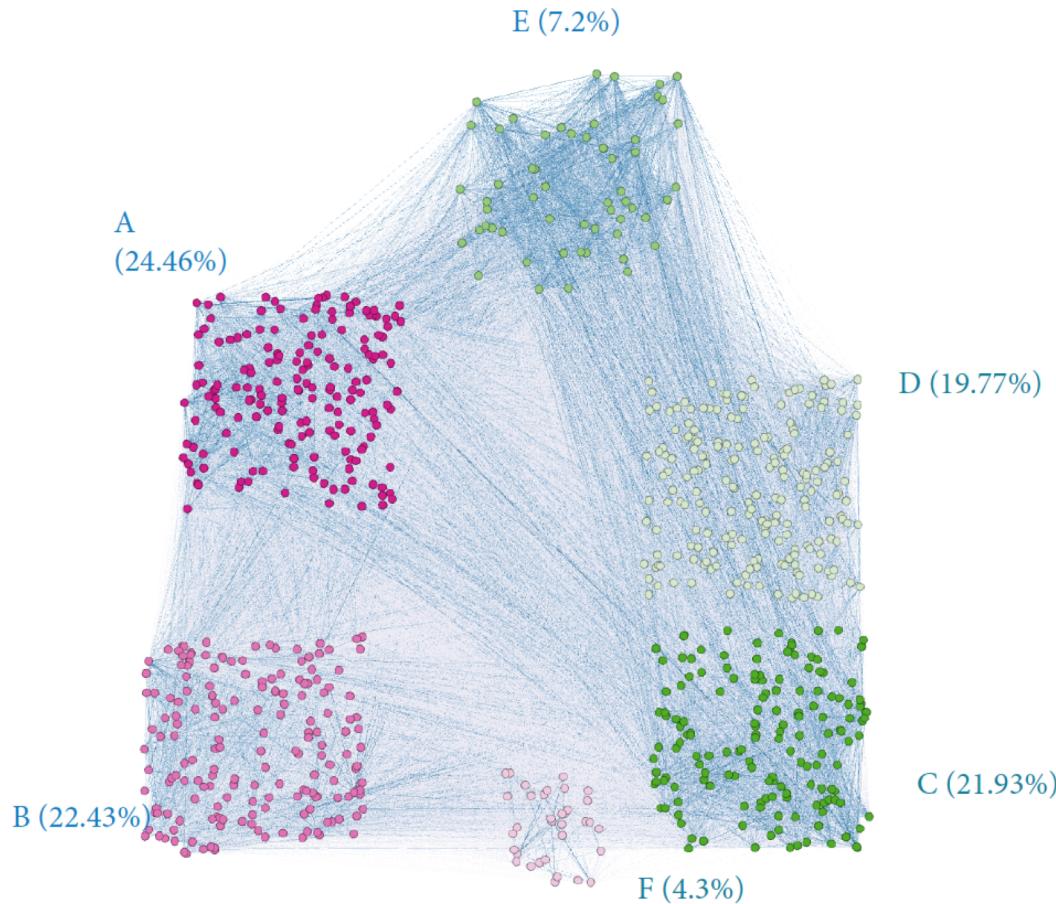
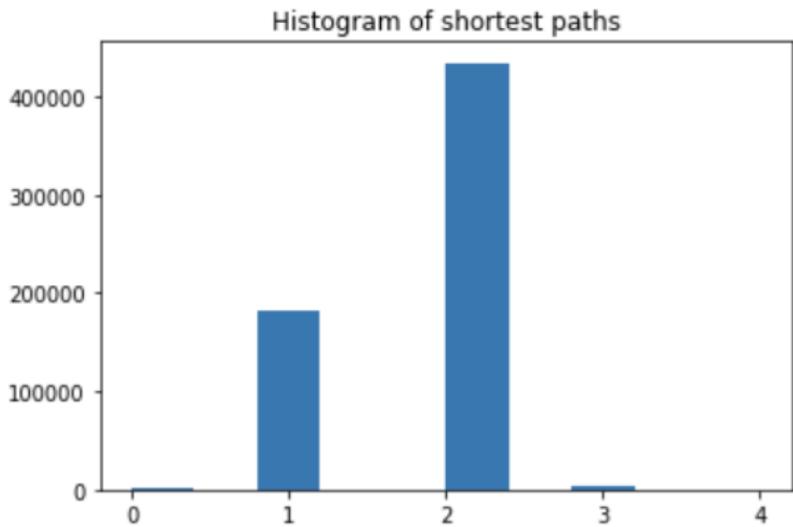


Figure 3. Coloring is, again, based on the Louvain clustering method. Edges are now colored according to their weight, where a darker edge means more interactions.

Small world property



	G_{random}	G_{school}
Avg clustering coefficient	0.381	0.499
Avg shortest path	1.62	1.62

Insights

- **Average shortest path** is 1.62 – every person at the school is reachable from infected person by approx. 1.6 hops
- **Small world property** holds in the graph, so disease could travel quickly

Simulation framework

Goals

- Model disease transmission based on base reproduction rate (R_0) by running simulation for ten timesteps
- Compare results depending on network role of first infected patient
- Compare results based on R_0

$$R_0 = \frac{\beta}{\mu} = \frac{2.7}{0.95} \approx 3$$

Simulation framework

Goals

- Model disease transmission based on base reproduction rate (R_0) by running simulation for ten timesteps
- Compare results depending on network role of first infected patient
- Compare results based on R_0

The diagram shows the formula for the base reproduction rate, $R_0 = \frac{\beta}{\mu}$. A blue arrow points from the left towards the symbol β , labeled "Base reproduction rate". Another blue arrow points from the right towards the symbol μ , labeled "Approximate R_0 for common cold". The fraction $\frac{2.7}{0.95}$ is highlighted in orange.

$$R_0 = \frac{\beta}{\mu} = \frac{2.7}{0.95} \approx 3$$

Simulation framework

Goals

- Model disease transmission based on base reproduction rate (R_0) by running simulation for ten timesteps
- Compare results depending on network role of first infected patient
- Compare results based on R_0

The diagram illustrates the calculation of the base reproduction rate (R_0) for the common cold. It features the formula $R_0 = \frac{\beta}{\mu} = \frac{2.7}{0.95} \approx 3$. Four arrows point to different parts of the formula: a blue arrow from the top left points to the term $\# \text{ infected by a single patient}$; a grey arrow from the bottom left points to the term $\text{Base reproduction rate}$; a blue arrow from the bottom right points to the term $\text{Recovery rate for infected}$; and a grey arrow from the top right points to the value 2.7 , labeled as $\text{Approximate } R_0 \text{ for common cold}$.

$$R_0 = \frac{\beta}{\mu} = \frac{2.7}{0.95} \approx 3$$

infected by a single patient

Base reproduction rate

Recovery rate for infected

Approximate R_0 for common cold

Simulation: First patient has high betweenness

- Assume the first infected patient has average degree and high betweenness
- Infection peaks at timestep 5, then drops slowly
- The slope of infection is around 8%
- High betweenness individuals have a greater impact on disease transmission dynamics

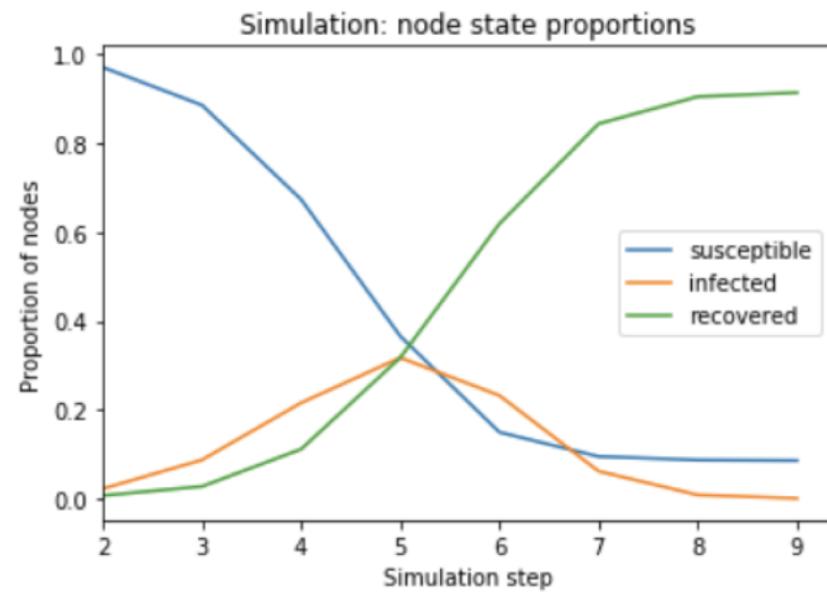


Figure 8. Transmission dynamics when first patient has high betweenness

Simulation: R_0 increases to 10

- Assume R_0 increases from 3 to 10, the approximate rate for mumps
- Infection peaks at timestep 3, then drops rapidly
- The slope of infection is around 20% per timestep
- In the real world, this would threaten to overwhelm capacity

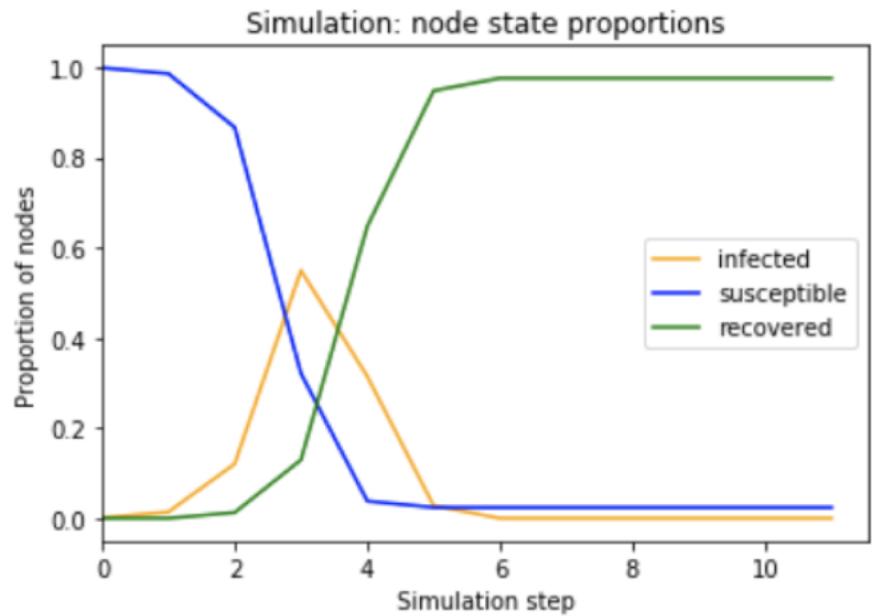


Figure 10. Transmission dynamics with $R_0 \approx 10$

Simulation Takeaways

	High Degree P_0	Avg Degree P_0	High Betweenness P_0	Five P_0	$R_0 = 10$
Peak	5	6	5	4	3
Infection slope	0.07	0.05	0.07	0.08	0.2

Insights

- Betweenness of initial patients and R_0 have a disproportionate impact on disease spread
- Though estimating betweenness is extremely difficult with prior data collection, R_0 can be estimated as more disease data is available

Recommendations and future work

- 1 Prioritize immunizing individuals with high centrality in the network (both degree and betweenness)
- 2 Test early and often to estimate R_0 as the epidemic breaks
- 3 Shut down colleges/high schools early during an outbreak since disease spreads rapidly in schools

Evolution of Global Petroleum Trade Network and its Communities

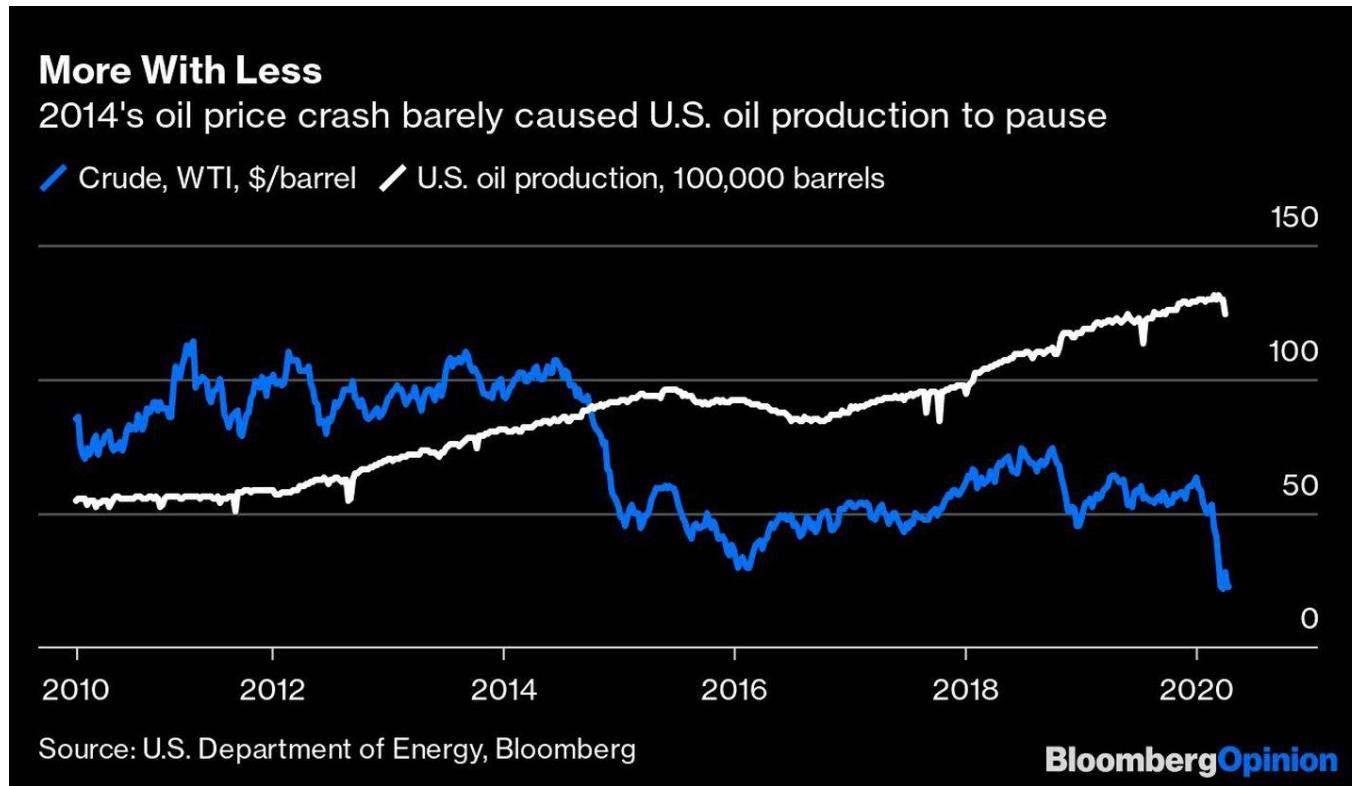
Candace Yee

Motivation



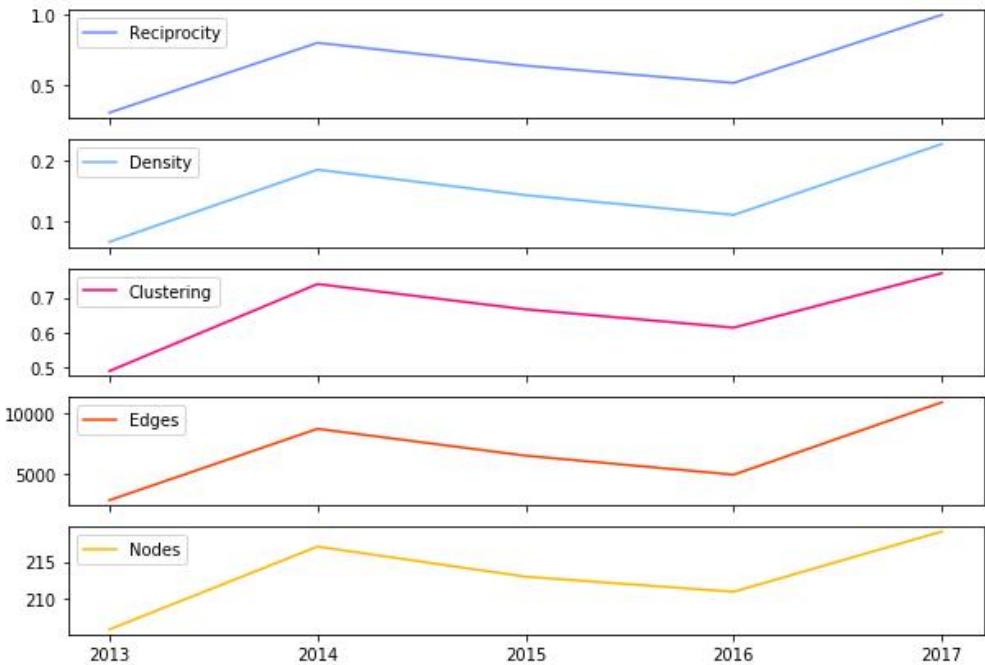
- petroleum is essential for electricity generation, transportation, etc., and is essential to the global economy

How does global petroleum trade change with oil price crashes?



Change in Networks from 2013-2017

Year	Nodes	Edges	Clustering	Density	Reciprocity
2013	206.0	2813.0	0.488354	0.066611	0.309278
2014	217.0	8717.0	0.738555	0.185975	0.802799
2015	213.0	6496.0	0.665790	0.143857	0.641318
2016	211.0	4924.0	0.613196	0.111126	0.519090
2017	219.0	10904.0	0.769793	0.228394	1.000000



- Kayla et. al (2012) used nodes, edges, clustering coeff., density and reciprocity to determine network stability over time

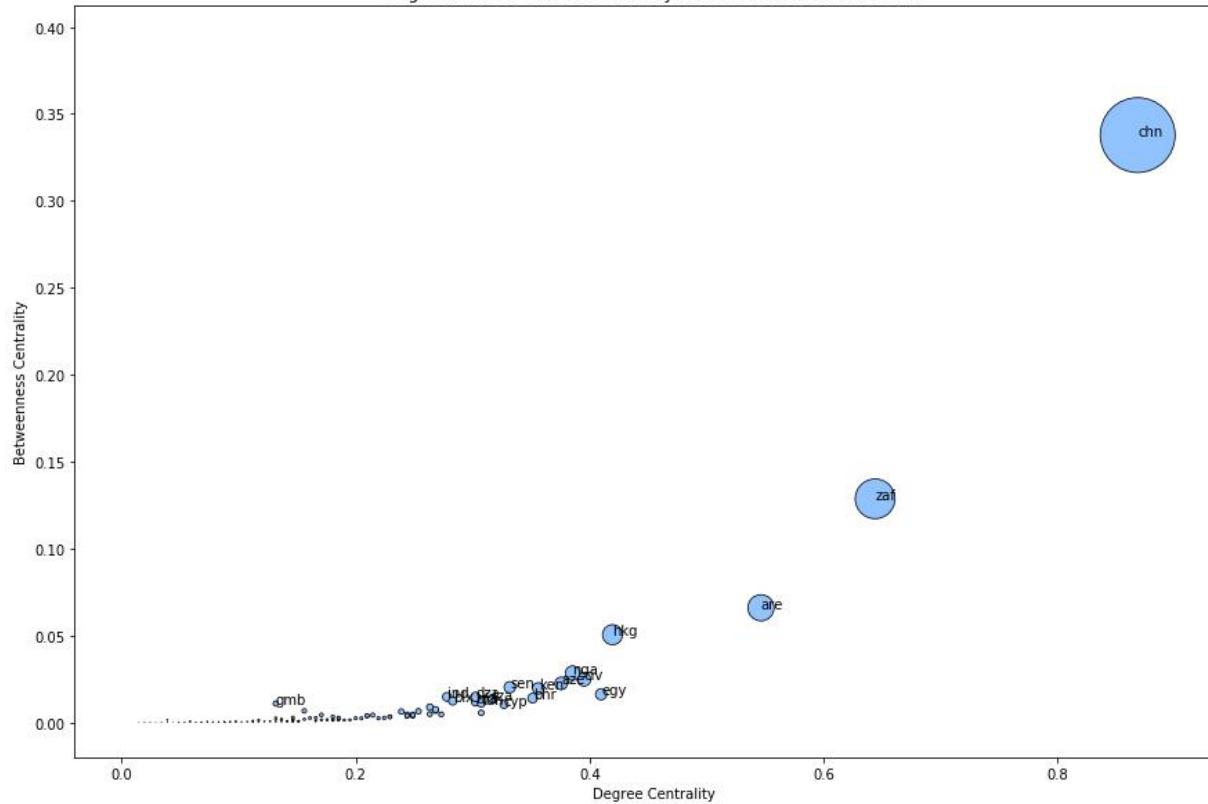
Hub vs. Authority Centrality in 2013 and 2016

		2013	2013 Hub Centrality	2016	2016 Hub Centrality		2013	2013 Auth. Centrality	2016	2016 Auth. Centrality
0	chn		0.036267	chn	0.023263	0	fra	0.016669	blx	0.014022
1	zaf		0.032309	ind	0.022926	1	ind	0.016459	fra	0.013738
2	are		0.030711	are	0.022575	2	blx	0.016450	deu	0.013630
3	egy		0.027772	kor	0.022322	3	nld	0.016295	are	0.013579
4	nga		0.025919	sgp	0.022276	4	gbr	0.016266	gbr	0.013459
5	hkg		0.024935	jpn	0.021618	5	usa	0.016021	tur	0.013377
6	aze		0.024292	mys	0.020046	6	deu	0.015815	nld	0.013356
7	civ		0.024054	zaf	0.020005	7	tur	0.015657	chn	0.013241
8	bhr		0.023718	tha	0.019211	8	chn	0.015283	ind	0.013232
9	ken		0.023457	egy	0.016679	9	esp	0.015245	usa	0.013224

- Kayla et. al (2012) also identified hubs (major exporters) and authorities (major importers) in their network.

2013

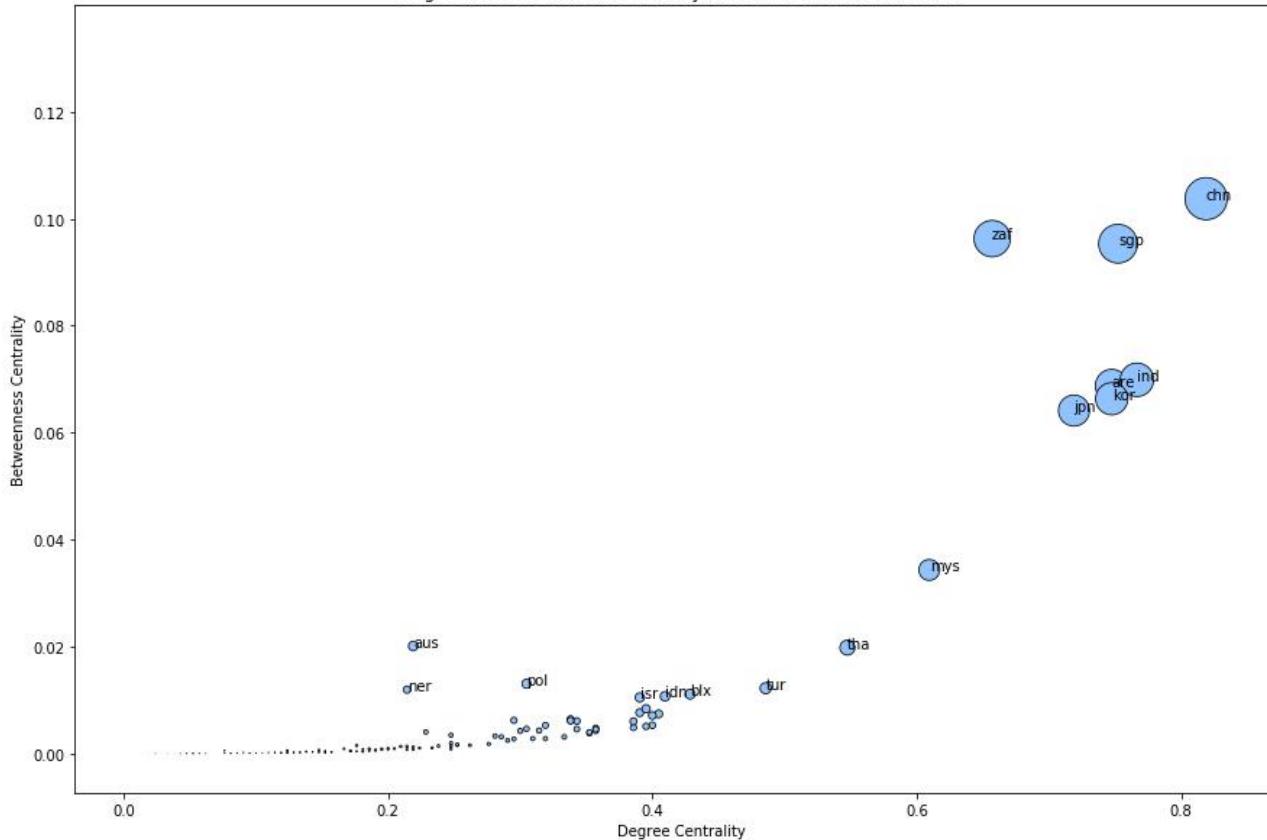
Degree vs Betweenness Centrality for Petroleum Trade Network



- In 2013, the leaders of the petroleum network, mainly China (CHN) and South Africa (ZAF), have relatively high betweenness and degree centrality

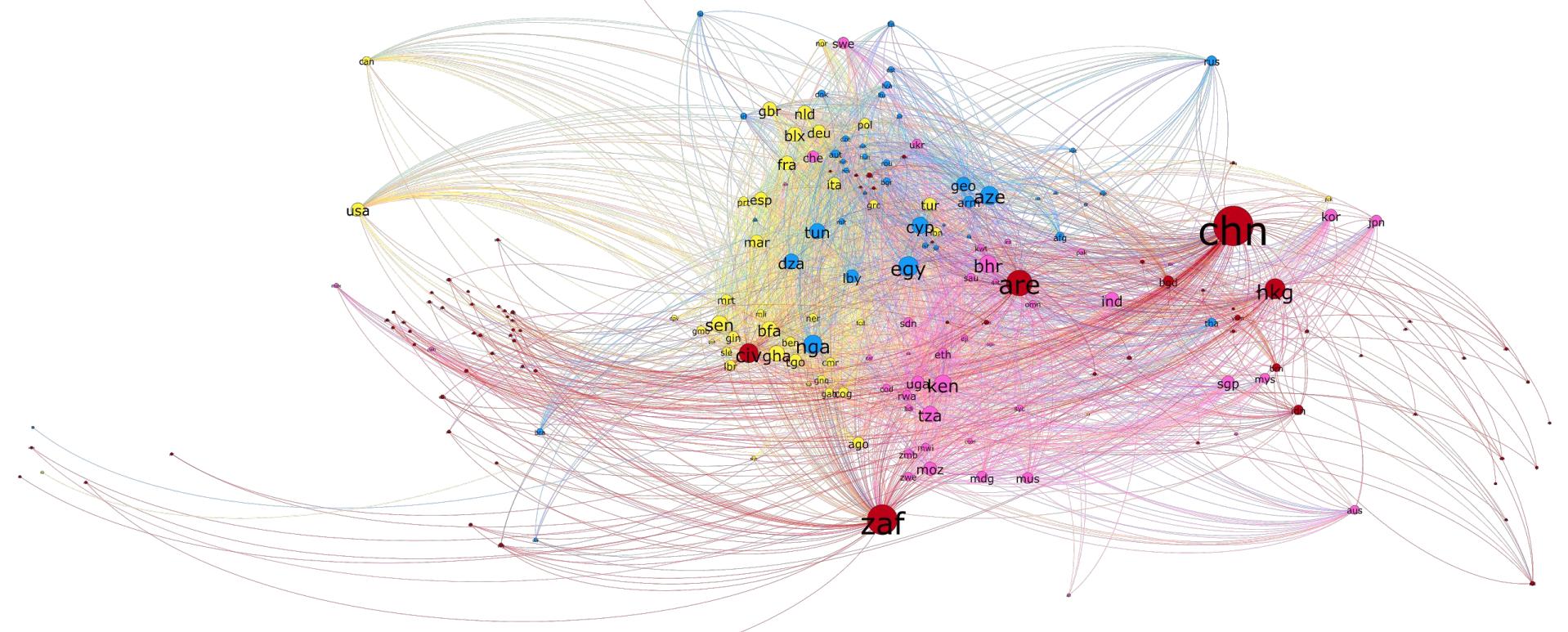
2016

Degree vs Betweenness Centrality for Petroleum Trade Network

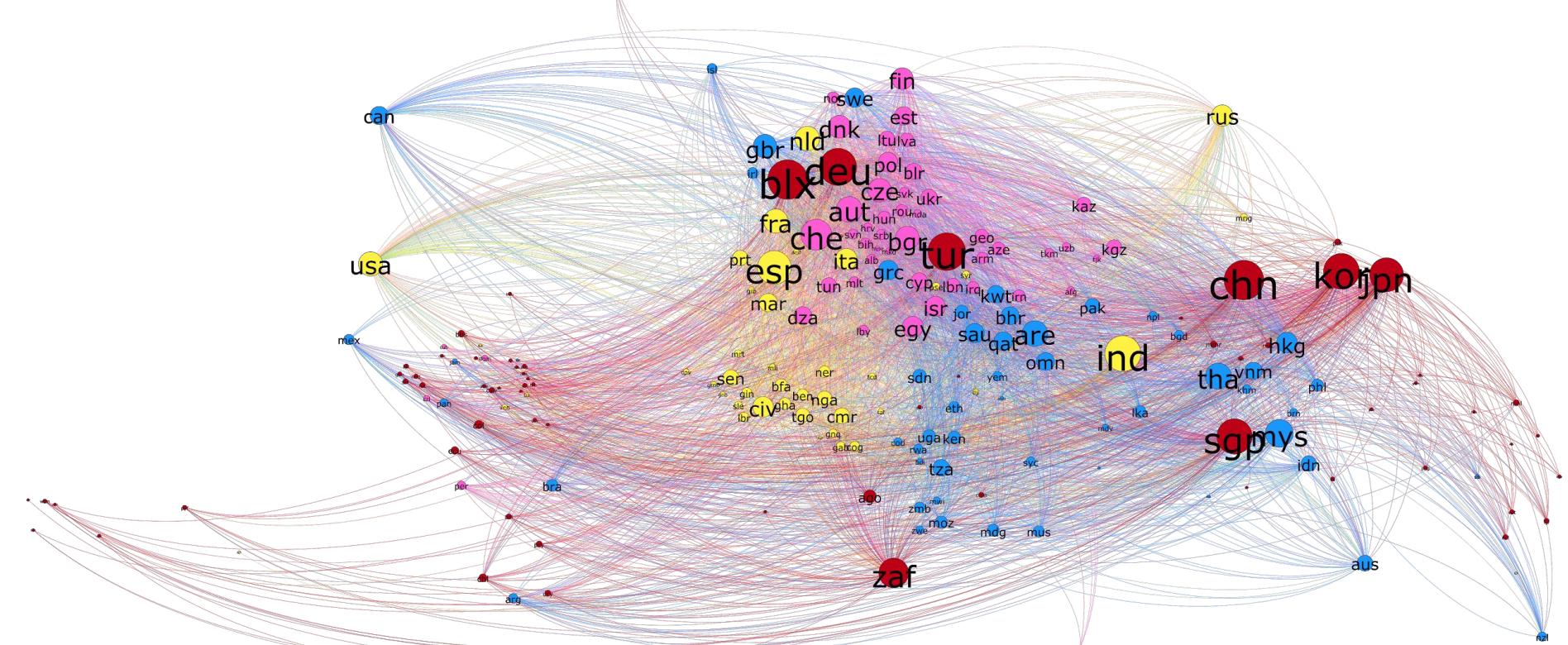


- In 2016, there are more countries that have high betweenness and high degree centrality, for example Japan and Singapore

2013



2015



2017

